PREDICTION OF GRINDING TEMPERATURE IN CERVICAL VERTEBRA BASED ON RBF NEURAL NETWORK

Heqiang Tian[1*], Jiakun Jiang[1], Xuanxuan Zhu[1], Longxin Ma[1], Chenchen Wang[1], Peng Yang[1], Sen Liu[2]

ABSTRACT: The accurate prediction of the grinding temperature in cervical vertebra is of great significance to prevention of tissue heat damage under high grinding temperature and the maintainence of grinding surface quality. According to the grinding heat transfer model of cervical vertebra, the main influencing factors of grinding temperature include grinding speed, grinding depth and moving speed. Based on MATLAB Neural Network Toolbox, a radial basis function (RBF) neural network prediction model was established by training the main parameters of grinding experiment, and the prediction error of the established model was analyzed in details. The verification experiments demonstrate that the minimum error RE_{min} is 6.59%, the maximum error RE_{max} is 8.42%, and the mean error *MAPE* is 7.61%. This means the proposed method can make reliable and accurate prediction of grinding temperature in cervical vertebra.

KEY WORDS: Cervical Vertebra; Grinding Temperature; Radial Basis Function (RBF) Neural Network; Prediction

1 INTRODUCTION

Recent years has witnessed the proliferation of grinding, a traditional way of accuracy machining, in surgical removal of bone tissues. In the course of grinding, a large amount of heat is produced on the grinding surface, posing thermal damages to bone tissues and adjacent tissues and nerves. To prevent the thermal injury, it is necessary to realize strict and precise control of bone grinding temperature.

The bone grinding process can be regarded as a common stage of material processing, in which the heat source moves on the grinding surface at the feed speed (Hou and Komanduri, 2000). Much research has been done by scholars at home and abroad in related areas. Rosenthal (1946) and Jaeger (1942) made prominent contributions to the research of moving heat sources, laying solid bases for the theoretical research of grinding temperature. Loewen and Shaw (1954) theoretically calculated the mean temperature of the contact area between shear surface and rake face. His research opens up a new way to calculate the theoretical grinding temperature and the distribution of grinding heat among chips, cutting tools and workpieces. Hong et al., (2000) established a linear inverse heat transfer model to predict grinding temperature distribution and heat flux along the grinding direction. Brosse et al., (2008) investigated the heat flux into the bone during grinding through the combination of the reverse heat transfer and infrared thermography. Zhang et al., (2013) established a heat transfer model and a finite element model, and forecasted the bone grinding temperature in the skull base neurosurgery by reverse heat transfer method. Based on finite element heat transfer model, Tai et al., 2013 projected the bone grinding temperature in neurosurgery with a heat transfer equation on the linear correlation between grinding heat and motor input energy.

To sum up, the grinding temperature has been determined mainly through direct measurement, computer simulation and theoretical calculation. There are many ways to directly measure grinding temperature. The infrared measurement, suitable for surface temperature, is difficult to capture the internal temperature of an object. Owing to its point shape, an infrared thermometer only supports mean temperature measurement of a point heat source. A thermocouple can gauge the internal temperature of an object, but in a point by point manner. Thus, it has to measure a series of points before forming a temperature field. The computer simulation model cannot simulate the exact temperature field of bone surface grinding, due to its marked differences from the real bones. The theoretical calculation of bone material grinding heat is severely constrained by the numerous influencing factors on grinding temperature and the complex non-linear function among parameters. For the absence of theoretical

[1] Shandong University of Science and Technology, Qingdao 266590, China
[2]Harbin Institute of Technology, Harbin 266590, China
[*]E-mail: thq_1980@126.com

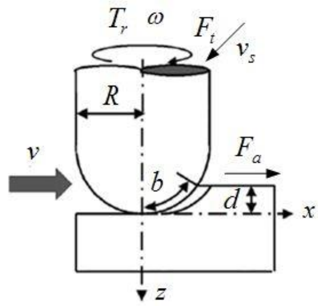
calculation model, the grinding temperature can only be approximated by the relatively mature metal grinding theory.

With powerful model training and prediction functions, the neural network is a desirable method for the grinding temperature of bone tissues (Fichera and Pagano, 2017). In the grinding process of cervical vertebra, there is a complex relationship among the many influencing factors on grinding temperature. Considering the primary factors and ignoring secondary ones, the radial basis function (RBF) can be introduced to approximate the complex relationship among the influencing factors. Based on the function, it is possible to create a neural network prediction model applicable to grinding temperature prediction of cervical vertebra.

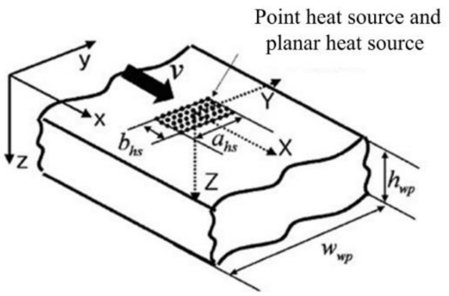
2 THEORETICAL ANALYSIS OF GRINDING TEMPERATURE OF CERVICAL VERTEBRA

The grinding temperature of cervical vertebra was discussed in details based on the moving heat source theory and heat transfer theory (Bonţiu and Lobonţiu, 2015; Trif et al., 2015). First, the primary influencing factors on bone grinding were obtained by ignoring the secondary ones. Then, the cervical vertebra grinding model and heat conduction control equation were constructed and simplied to quantify these primary factors. These steps lay the basis for the establishment of RBF neural network prediction model.

Medical drill is a common grinding tool in bone surgeries. The globular diamond grinding head causes little trauma to the soft tissue. However, the diamond grinding tool produces a huge amount of heat in the grinding process, which complicates the analysis of grinding deformation in 3D space. Unlike metal grinding, bone tissue grinding has an entirely different heat source. For example, the grinding heat of cervical vertebra is mainly released from the plastic deformation of shear surface. For simplification, the cervical vertebra grinding process is viewed an $a_{hs} \times b_{hs}$ rectangular heat source moving at speed v along a $w_{wp} \times h_{wp}$ semi-infinite surface. The grinding heat transfer model is illustrated in Figure 1.



(a) Grinding principle



(b) Heat transfer model

Figure1.Grinding heat transfer model of cervical vertebra

During the grinding of cervical vertebra, the heat from convection and radiation is so small as to be negligible. Thus, only the effect of heat conduction was taken into consideration. The heat conduction equation of cervical vertebra grinding is a partial differential energy equation under Cartesian coordinate system (Nayak, 2016):

$$\rho c\left\{\frac{\partial T}{\partial t}+(v\nabla)T\right\}=k\nabla^2 T \tag{1}$$

Where ρ is density of cervical vertebra; c is the specific heat of cervical vertebra; v is the moving speed of the heat source; k is the thermal conductivity of cervical vertebra.

According to the grinding heat transfer model in Figure 4, the input heat of the moving heat source in the grinding can be obtained as follows:

$$q_w=\varepsilon q_{total}=\varepsilon\frac{F_t v_s}{a_{hs}\times b_{hs}}\approx\varepsilon\frac{F_t v_s}{2b^2}$$
$$=\varepsilon\frac{(cd)(\omega R)}{2b^2}=(c\varepsilon R)\frac{d\omega}{2b^2}$$

(2)

Where F_t is the tangential cutting force; d is the grinding depth; c is a constant; ε is heat distribution ratio; v_s is circular linear speed; ω is grinding speed; R is the radius of medical drill; b is the contact length of medical drill grinding; b is the function between R and d. $b_{hs}\approx d$; $a_{hs}\approx 2b$; the tangential cutting force is proportional to the grinding depth, that is, $F_t=cd$.

According to Ehrhard's (1993) statement that a plane heat source is composed of numerous point heat sources, the approximate solution $T(X, Y, Z)$ of Equation (1) can obtained, which involves grinding speed ω, moving speed v, the characteristic parameters of cervical vertebra (e.g. thermal conductivity k), and the structure parameters of medical drill (e.g. drill radius R). In the solution, $(X, Y, Z)=\{(x+vt), y, z\}/h_{wp}$ and h_{wp} is thickness of cervical vertebra.

Through the above theoretical analysis on grinding temperature, the main influencing factors of the grinding temperature include grinding depth d, grinding speed ω, moving speed v, the structure parameters of the medical drill (e.g. radius R), and the characteristic parameters of cervical vertebra (e.g. thermal conductivity k and density ρ).

From Equation (2), it can be seen that the grinding temperature surges up with the increase in grinding speed and grinding depth. If the grinding picks up speed, the feed rate will grow, and the grinding temperature will increase. Meanwhile, the grinding temperature is also affected by the structure parameters of medical drill, and the characteristic parameters of cervical vertebra (Equation (1)).

Since the structure parameters and characteristic parameters are fixed, the grinding temperature mainly depends on grinding depth d, grinding speed ω and moving speed v. Therefore, these three factors were taken as the input parameters of the RBF neural network used to predict the grinding temperature of cervical vertebra.

3 RBF NEURAL NETWORK PREDICTION MODEL OF GRINDING TEMPERATURE

According to the grinding heat transfer model of cervical vertebra, there is a nonlinear relationship among the influencing factors on grinding temperature. In light of this, the temperature prediction can be done by means of statistics, data fitting, neural network, etc.The most viable solution lies in the RBF neural network, which can approximate any nonlinear relationship with any accuracy (Sun et al., 2016). Featuring simple structure, rapid training, and fast convergence, the network boasts the best approximation effect in the modeling and identification of nonlinear problems.

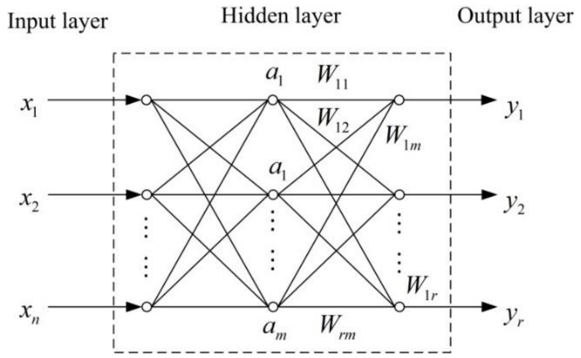


Figure 2. RBF neural network structure

As shown in Figure 2, the RBF neural network is a three layer feed-forward neural network. The three layers, namely an input layer, a hidden layer and an output layer, realize two layer-mappings.

The first layer-mapping is a nonlinear mapping from the input layer X to the hidden layer a_i:

$$X \to a_i = \psi_i\left(\left\|X - c_i\right\| / b_i\right) \tag{3}$$

The second layer-mapping is a linear mapping from the hidden layer a_i to the output layer Y:

$$Y = Wa = \sum_{i=1}^{m} \omega_{ji} a_i \left(j = 1,2,\cdots,r\right) \tag{4}$$

Where X is the n-th dimension input vector (x_1, x_2,…x_n); a is the output (a_1, a_2,…a_m)of the m-th dimension hidden layer node; Y is the r-th dimension input vector (y_1, y_2,…y_r); ψ_i is a symmetric radial basis function; c_i is the vector whose the i-th basis function centre has the same dimension with X; b_i is the optimal clustering result obtained by the K-means clustering method; $||X-c_i||$ is the norm of X-c_i; ω_{jt} is the weight of the i-th hidden node to the j-th output.

The prediction accuracy of the model was evaluated against the relative error percentage (RE) and the mean absolute percentage error (MAPE):

$$RE = \frac{\left|y_i - y_i^{'}\right|}{y_i} \times 100\% \tag{5}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|y_i - y_i^{'}\right|}{y_i} \times 100\% \tag{6}$$

Where n is the sample size; y_i is the true value; $y_i^{'}$ is the predicted value.

To disclose the hidden relationship between input and output data, the RBF neural network was adopted to model these data of the direct training system. The training purpose is to minimize the prediction error. In this research, the prediction object is the grinding temperature. There are three nodes on the input layer: the grinding depth d, the grinding speed ω or n, and the moving speed v. The network has only one output: the grinding surface temperature of cervical vertebra. Figure 3 presents the structure of neural network prediction model of grinding temperature.

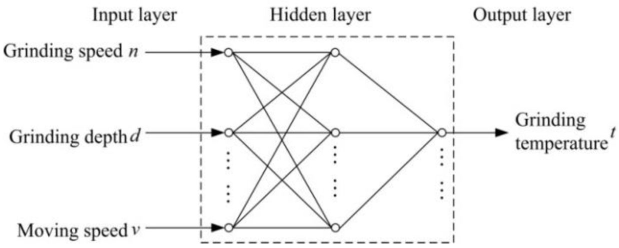


Figure3. Structure of neural network prediction model of grinding temperature

The RBF neural network prediction model of grinding temperature was established with the MATLAB toolbox. For better prediction accuracy, the optimal structure form was determined by adjusting the width coefficient SPREAD in the function newrb (P, T, GOAL, SPREAD, MN), where P is the training sample, T is the target sample, GOAL is the accuracy grade, SPREAD is the width coefficient of radial basis function, and MN is the maximum number of neurons.

4 PREDICTION AND ANALYSIS

4.1 Training data acquisition and normalization

To detect the cervical bone grinding temperature, the author designed and built a test platform for cervical vertebra grinding temperature. Based on the grinding temperature detected on the platform, the input and output data were provided for the neural network prediction model by setting grinding speed, grinding depth and moving speed.

The test platform consists of a temperature measurement module, a grinding speed control module, a feed speed control module and a radial grinding depth control module (Figure 4). The medical drill was customized to minimize the trauma to soft tissue. It has a 2mm-diameter shaft and a 4mm-diameter diamond grinding head. The grinding head was subject to open-loop speed control, and driven by a high temperature sterilization series brushless DC motor (Maxon EC22 50W) with Hall Effect sensors. The grinding temperature was measured by a dual channel thermocouple thermometer (TC-127U) with a range of -200℃~1,372℃ and an accuracy of 0.1℃. Two thermocouples were separated by 15mm to reduce the mutual influence. The pig spine was clamped on the guide rail of ball screw by a clamping device, which can move at a constant speed along the rail. The moving speed was obtained by controlling the motor feed speed. The grinding speed was configured in the grinding speed control module of the host computer, and the grinding depth was adjusted in the radial grinding depth control module.

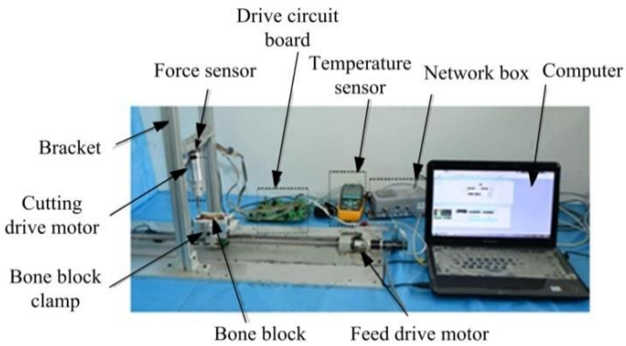


Figure4. Temperature detection test platform for cervical vertebra grinding

The experiment was conducted by the single-factor variable control method. In other words, one of the parameters was adjusted to detect the variation in grinding temperature without changing the other parameters. As mentioned above, grinding speed, grinding depth and moving speed were taken as the training input parameters, and grinding temperature was taken as the output data. The input data settings are listed in Table 1 below. With 5 values for each input parameter, a total of 125 sets of input data were obtained by the single factor variable control method.

Table 1. Input parameters of neural network prediction model

Parameter names	Value				
Grinding speed (r/min)	2000	4000	6000	8000	10000
Grinding depth (mm)	0.2	0.4	0.6	0.8	1.0
Moving speed (mm/min)	20	40	60	80	100

Theoretically, the radial basis function may have an obvious output if the distance of the numerical value from the centre of the function is below a certain threshold. In this research, the data were normalized by equal-ratio transformation method. Each data set was mapped into the linear space [-1, 1] by the transformation below:

$$x_i^{'} = \frac{(x_i - x_{mid})}{(x_{\max} - x_{mid})} \quad (7)$$

Where x_{min} and x_{max} are the maximum and minimum value of the data set, respectively. x_{mid}=0.5(x_{min}+x_{max}).

4.2 Prediction results

The sample training was carried out with MATLAB Neural Network Toolbox. The training process is described as follows: First, the sample information was weighted to form the input data into the hidden layer; then, the input data was mapped by the radial basis function to produce the output information of the hidden layer; finally, the output information was weighted and transmitted into the output layer; after that, the weighted output information was linearly combined to yield the output data of the output layer.

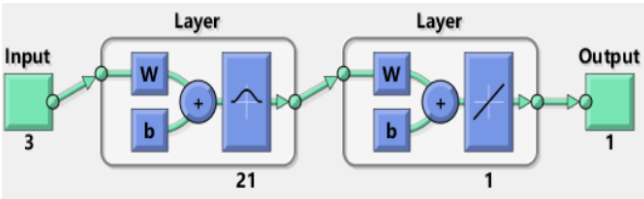


Figure 5.Training structure diagram

According to the training structure in Figure 5, the cervical vertebra temperature prediction neural network has 3 input parameters, 1 output parameter, and 21 hidden layer nodes. The tolerable error was set to1e-8, the diffusion factor to 22, and the maximum number of neurons to 21. After calling the radial basis function, the number of nodes in the network kept growing until the training error fell below the tolerable error.

Before applying the proposed model in prediction and control of grinding temperature, it is necessary to evaluate its prediction accuracy through error analysis and comparison of predicted results. The error analysis aims to determine the prediction accuracy of the model, and ensure the practicality of the predicted results.

In the given range of grinding speed, grinding depth and grinding speed, three sets of data were randomly selected to form three groups of grinding parameters. The parameter values were all different from the sample values in the prediction experiment. The grinding parameters and results are shown in Table 2. Through calculation, it is obtained that the RE_{min} between predicted results and experiment results is 6.59%, the RE_{max} is 8.42%, and the *MAPE* is 7.61%. These errors are attributable to three factors: model selection, data processing error and data measurement error.

Table 2. Comparison of grinding temperature results

Serial number	Grinding speed (r/min)	Grinding depth (mm)	Moving speed (mm/min)	Predicted temperature (℃)	Measured temperature (℃)	Error rate
1	1000	0.1	10	24.1	25.8	6.59%
2	3000	0.2	30	33.1	35.7	7.28%
3	5000	0.5	50	48.5	52.5	7.62%
4	7000	0.7	70	55.4	60.3	8.13%
5	9000	0.9	90	65.2	71.2	8.42%

(1) Model selection

The proposed model can basically express the relationship between grinding temperature and influencing factors. However, it is impossible to contain all factors in the model because of the complexity of grinding process and the uncertainty of influencing factors. Hence, the secondary factors were ignored before the establishment of the empirical grinding model.

(2) Data processing error

Limited by computing power and data accuracy, data truncation errors existed in the normalization of input data and the training of the RBF neural network. In addition, some errors arose from the sample size and other reasons.

(3) Data measurement error

The sensing of grinding temperature was subject to certain interference from the difference between measurement methods, the installation of sensor, and the measurement accuracy.

5 CONCLUDING REMARKS

Owing to the complex situations of the bone surgery, the surgical objects are bound to vary in bone features. The soft tissues, blood and other factors have made it difficult to build an accurate prediction model of bone grinding temperature. To overcome the difficulty, this paper establishes a RBF neural network prediction model of grinding temperature based on bone grinding heat transfer model. Through the verification experiments, it is known that the RE_{min}, RE_{max} and *MAPE* of the predicted grinding temperature in cervical vertebra were 6.59%, 8.42% and 7.61%, respectively. This means the proposed method can make reliable and accurate prediction of grinding temperature in cervical vertebra.

6 ACKNOWLEDGEMENTS

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